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Is default risk priced equally fast in the credit default swap and the stock markets? AN empirical investigation

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ABSTRACT

We examine whether default risk is priced equally fast in the credit default swap (CDS) and the stock markets in the main economic sectors of North America, Europe, the UK, and Asia. We find significant evidence in all of these regions and economic sectors that the stock market leads the price discovery process because it reflects default risk faster than the CDS market. We also find weak evidence that the documented lead-lag relation is not regime-dependent and that is stronger for negative stock market news. Our findings do not confirm the theoretical prediction that the CDS market responds faster than the stock market to changing credit conditions. Consistent with the market selection theories, our findings imply that informed traders prefer to trade default risk mostly in the stock market but uninformed traders mostly in the CDS market.

1. Introduction

This paper examines whether default risk is priced faster in the credit default swap (CDS) market or the stock market. In frictionless markets, the prices of CDS and stock prices should be closely related because they depend on the distribution of the market value of the firm's corporate assets. In particular, large CDS spreads should be related to a stock's low valuation and/or high volatility and vice versa. Under both scenarios the arrival of information that is related to changing default risk should instantly and simultaneously be absorbed by the two markets, and the stock returns and the CDS spread changes should be contemporaneously correlated but not cross-autocorrelated. However, if one market processes information more efficiently than the other, then it can price the changing default risk faster than the other. The actions of informed traders can then lead to a lead-lag relation between the returns of the two markets.

A CDS is a contract that allows the transfer of credit exposure between two parties on a particular firm or country (i.e., the reference entity). The buyer of a CDS periodically pays a premium to the seller of the CDS until the maturity of the contract (i.e., bond) or the occurrence of a credit event; whichever comes first. In the case of a credit event the buyer of the CDS receives compensation for the loss incurred equal to the difference between the nominal value of the bond and its market value after the occurrence of the credit event.[1] The CDS spreads are determined solely by default risk. Further, the CDS market

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[1] According to the (ISDA, 2014) a credit event can take the form of a bankruptcy, obligation acceleration, obligation default, failure to pay, repudiation or moratorium (for sovereign entities), or a restructuring. The most important credit event is the restructuring of debt because it does not always or immediately lead to a loss for the CDS holder.

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is highly liquid with many sophisticated investors (Kapadia and Pu, 2012).[2] Thus, the theorectical prediction is that the CDS market leads the stock market in pricing default risk. On the other hand, equity holders are residual holders of the assets of a firm, and therefore they should also be very concerned about a firm's probability of default. Hence, they are likely to monitor a firm's default risk more than its creditors who typically hold senior claims or other guarantees. Under this scenario, the stock market should lead the CDS market. This is consistent with the theories on market selection (Easley et al., 1998), which state that if informed traders prefer to trade in only one market, for reasons that include transaction costs, liquidity, mechanisms, leverage, and insider trading legislation, then this market reflects the most recent information. Thus, the lead of one market over another indicates that the informed traders are active mainly in this particular market, and therefore this market leads the price discovering process.

Despite the growth in the literature on the relation between the CDS market and other markets, empirical evidence on the lead-lag relation between the stock and the CDS markets is still unclear (e.g., Hilscher et al., 2015; Longstaff et al., 2003; Forte and Lovreta, 2015; Forte and Peña, 2009; Marsh and Wagner, 2015; Norden and Weber, 2009, 2004; Flannery et al., 2010; Byström, 2008). Thus, the motivation for our study is to add to the literature by using a large data set that covers nine main economic sectors in North America, Europe, Asia, and the UK. Our study uses the highly liquid Thompson Reuters CDS indices and manually constructs the underlying stock portfolios to examine whether default risk is priced equally fast by the CDS and the stock markets. We use a bivariate vector autoregression system to examine the relation between the daily stock returns and changes in the daily CDS spreads. Specifically, we address the following two questions: (i) Is there a lead-lag relation between the CDS and the stock markets? And (ii) is the lead-lag relation between the CDS and stock markets different across different geographical regions and economic sectors? We find that the daily stock returns lead the daily CDS spread changes. We also find weak and mixed evidence that the changes in the daily CDS spreads lead the daily stock returns. This asymmetric relation holds in all of the geographical regions and economic sectors. We also find weak evidence that the documented lead-lag relation is not regime-dependent and that is stronger for negative stock market news. Overall, the results indicate that the stock market prices changing default risk faster than the CDS market. Thus, it seems that the stock market is relatively more efficient in processing information than the CDS market and therefore leads the price discovering process. Similar to Hilscher et al. (2015), our results are consistent with the theories on market selection according to which informed traders participate mostly or only in one market. Hence, our results also support the view that the stock market is dominated by informed traders of default risk, while uninformed traders of default risk (i.e., liquidity traders) participate mostly in the CDS market.

Our paper makes several contributions. First, we examine which market leads the price discovery process by using the highly liquid Thomson Reuters (TR) CDS indices rather than firm-level CDS. Indeed, most previous studies use firm-level data of usually a low number of obligors.[3] The use of the TR CDS indices helps to mitigate any adverse effects due to nonsynchronous data, stale quotes, and extreme differences in the liquidity of single-name CDS that could affect the interpretation of the observed lead-lag relations.[4] The possible nonsynchronous data in the CDS and the stock markets may lead to cross-autocorrelation between the CDS spread changes and the stock returns, and to spurious results related to the lead-lag relation of the CDS and stock markets. Instead, the CDS indices we use in our paper are made up from a large cross-section of single-firm CDS, which helps to minimise the adverse effects of nonsynchronous trading and stale quotes[5]. Further, the TR CDS indices are rebalanced every six months, and therefore timely reflect changes in the liquidity in the CDS market. Second, our examination covers a longer time period (i.e., January 2008 to June 2014) compared to the time periods covered by past research.[6] This time period covers the credit crisis and is an appropriate period for ensuring the robustness of the documented lead-lag patterns. Third, we expand the previous literature by using a large and comprehensive database that covers nine major economic sectors in North America, Europe, Asia, and the UK. As far as we are aware, most of prior literature focuses on fewer geographical

[2] According to the Bank for International Settlements (BIS, 2014a), the size of the CDS market, based on notional amounts outstanding, increased substantially from $6.4 trillion in 2004 to $58.2 trillion in 2007, and then started to gradually decrease to reach $21.0 trillion at the end of 2013, and $19.0 trillion at the end of June 2014.The observed reduction in the notional size of the CDS market during the last six to seven years can be mainly attributed to the effects of portfolio compression and not to the actual shrinking of the CDS market. Portfolio compression (also known as trade tear-ups) aims to improve the risk management of derivatives positions, and the BIS defines it as the "*process for tearing up trades, which enables economically redundant derivative trades to be terminated early without changing the net position of each participant*" (BIS, 2014b). The mechanisms of portfolio compression involve the termination of existing trades and their replacement with a smaller number of new trades of a smaller notional amount but with the same default risk profile and cash flows as the initial portfolio. As a result, portfolio compression reduces the overall notional size and the number of outstanding contracts in derivatives portfolios.

[3] Norden and Weber (2009) use a sample of 58 international firms; Norden and Weber (2004) use a sample of 90 firms; Forte and Peña (2009) use a proprietary sample of 17 North American and European non-financial firms; Forte and Lovreta (2015) use a sample of 643 firms; Marsh and Wagner (2015) use a sample of 193 firms; Hilscher et al. (2015) use a sample of 800 firms; Longstaff et al. (2003) use a sample of 67 North American firms; Jorion and Zhang (2007) use a sample of 820 obligors.

[4] Hilscher et al. (2015) argue that price data from CDS and stock markets may not be synchronized perfectly on a daily basis. Possible explanations of the delay in the adjustment of the CDS quotes to publicly available stock prices include the lack of trading, and the slow diffusion of default risk related information across markets and industries (Hou, 2007). The slow information diffusion might be due to market frictions, limited CDS and stock market participation, asymmetric information, noise traders (especially in the stock market), trading costs, short sales restrictions, and the legal restrictions faced by institutional investors.

[5] Cross-sectionally, the TR CDS indices we use in our study are made up of 395 North American, 184 European, 73 UK, and 179 Asian obligors.

[6] Byström (2008) covers the time period June 2004 to August 2005; Marsh and Wagner (2015) cover the time period January 2004 to October 2008; Longstaff et al., (2003) cover the time period March 2001 to October 2002 ; Norden and Weber (2009, 2004) cover the time period 2000–2002; Forte and Peña (2009) cover the time period September 2001 to June 2003; Forte and Lovreta (2015) cover the time period 2002–2008; Marsh and Wagner (2015) cover the time period 2004–2008; Hilscher et al., (2015) cover the time period 2001–2007.

regions and economic sectors.[7] This makes our results and inferences easier to be generalised, while it also allows for cross-country and cross-sector comparisons. Fourth, the use of CDS indices allows us to focus on market-wide credit risk rather than firm-specific credit risk. The CDS market is solely affected by credit risk, and Vassalou and Xing (2004) and Fiordelisia and Marqués-Ibañez (2013) present evidence that credit risk is systematic and therefore should also be priced in stock prices.

A better understanding of how default risk is priced by the CDS and the stock markets is important for market participants and policy-makers. A statistically significant lead-lag relation between the two markets implies informational inefficiencies and signals profitable opportunities from trades in the two markets. For example, if a lead-lag relation between the CDS and the stock markets exists then it might be possible that speculators take directional bets on default risk without having to take on direct exposure to the underlying reference entity. Further, when CDS traders are concerned about changes in default risk, they might look for signals in the stock market. In particular, arbitragers might benefit by investing in the lagging market, while hedgers can manage their credit risk exposure to the stock market. Our results are also interesting to regulators because the outbreak of the financial crisis showed that speculation in the CDS market might spread risk to the bond and stock markets. Thus, the insights into the relative efficiency of the CDS and stock markets might be used for better monitoring of risk transference and to promote policies that might enhance pricing efficiency. Further, our results indicate the presence of informed traders in the stock market and the general lack of informed traders in the CDS market. Because we find that the CDS market does not have predictive power for stock returns, our results are inconsistent with the view that trading (and speculation) in the CDS market might magnify the turbulence in the stock market.

This paper is set out as follows. Section 2 presents and discusses the relevant literature. Section 3 describes the dataset we use in our paper. Section 4 describes the methodological approach we follow, and presents and discusses the empirical results. Finally, Section 5 summarizes and concludes our paper.

2. Related literature

The main motivation of our study is the rather inconclusive results of past research on the ability of the CDS and the stock markets to price default risk relative to each. For example, Byström (2008) uses seven European sectoral iTraxx CDS indices and the underlying stock portfolios and finds that the stocks incorporate firm-specific information faster than the CDS. Norden and Weber (2009) use an international sample of 58 firms and find that stock returns lead the changes in the CDS and bond spreads.[8] Their results are stronger for US than for European firms. They also find that the sensitivity of the CDS market to past stock market movements is significantly related to the firm's credit quality and the size of its debt. Forte and Peña (2009) use a proprietary sample of North American and European firms and find that stocks lead the CDS more frequently than the other way around. Further, Marsh and Wagner (2015) use daily data for 900 US entities and find that US equity returns robustly lead CDS returns. They also find that this is due to common rather than firm-specific news, and that this lead-lag relation arises predominantly for positive equity market news. More recently, Hilscher et al. (2015) provide evidence that informed traders trade mainly in the stock rather than the CDS market. This strand of the literature clearly indicates that the stock market is relatively more efficient than the CDS market in processing information related to default risk changes. This higher efficiency of the stock market relative to the CDS market might be due to the different informational environments and the types of investors that dominate in each market. Specifically, there are more stock analysts in the stock market than credit analysts in the debt market. Further, stock analysts revise and disseminate their beliefs about the default risk of firms more frequently than credit analysts who tend to disseminate their recommendations periodically. Thus, it is likely that the information related to changing default risk is processed faster in the stock market than in the CDS market, which might react with a time lag. Additionally, Hilscher et al. (2015) show that the stock market prices default risk faster than the CDS market mainly because the informed traders are deterred from trading in the CDS market due to the high spreads.[9] A partial explanation could also be the assumption of slow diffusion[10] of default risk related information across markets and industries that may lead to nonsynchronous trading in the CDS and the stock markets (Hou, 2007).

On the other hand, Longstaff et al. (2003) use a sample of 67 North American companies and present no clear cut evidence that the stock market leads the CDS market.[11] Interestingly, Forte and Lovreta (2015) find that the stock market's lead holds only in periods of financial turbulence, while in tranquil periods the CDS market is equally or more efficient than the stock mar-

[7] Norden and Weber (2009) employ an international sample of 58 firms from the sectors: financials, telecoms, and automotive; Forte and Peña (2009) use a proprietary sample of 17 North American and European firms; Norden and Weber (2004) use a sample of 90 North American, European, and Asian firms from the sectors: financials, telecoms, automotive, utilities, chemicals, retailers; Byström (2008) employs European CDS indices that cover the sectors: automotives, energy, technology and media telecommunications, consumers, senior financials and sub-ordinated financials; Marsh and Wagner (2015) use data for 900 US entities from the sectors: basic materials, consumer goods, consumer services, financials, health care, industrials, oil and gas, technology, and utilities; Longstaff et al. (2003) use a dataset of 68 North American firms from the sectors: financials, technology, energy, defence, hotels, retail, transportation, and basic industries.

[8] Specifically, they find that individual stock returns have predictive power for changes in CDS spreads in 39 cases, while individual changes in CDS spreads have predictive power for stock returns in only five cases.

[9] Bid-ask spreads in the CDS market might be high because the market makers want to discourage informed traders from trading in the CDS market, and to reflect the high order processing and inventory costs in the CDS market due to the lower volume compared to the stock market volume.

[10] The slow information diffusion might be due to market frictions, limited CDS and stock market participation, asymmetric information, noise traders (especially in the stock market), trading costs, short sales restrictions, and the legal restrictions faced by institutional investors.

[11] In particular, they find that changes in CDS spreads were able to predict stock returns in 10 of the 67 firms in their sample. In contrast individual stock returns were able to forecast CDS spread changes in 12 of the 67 single-name CDS.

ket. Flannery et al. (2010) find that the CDS and stock markets are, in general, equally efficient, and if anything, the CDS market has a stronger impact on the stock market instead of the other way around. Jorion and Zhang (2007) find that large changes in CDS spreads are followed by large stock market movements when credit deterioration is anticipated. Further, Acharya and Johnson (2007) use 79 North American single-name CDS and find that the CDS market leads the stock market in the case of negative firm-specific news; also supported by Qiu and Yu (2012). Norden and Weber (2004) use an international sample of 90 firms and find that both the CDS and the stock markets anticipate credit downgrades and reviews on downgrades (similar results are reported by Hull et al., 2004). The different findings of this strand of the literature may be due to reasons that make the interpretation of the empirical results in the literature rather difficult and even misleading. For example, Trutwein et al. (2011) find that the relation between the CDS market and the stock market is regime dependant and that the stock prices anticipate large CDS spread changes; similar findings are reported by Forte and Lovreta (2015) and Alexander and Kaeck (2008). It might also be possible that the relation between default risk and stock returns is highly nonlinear and therefore is not adequately captured by the models used in the literature (see, e.g., Chen and Hill, 2013; Garlappi and Yan, 2011; Vassalou and Xing, 2004; Dichev, 1998). Fung et al. (2008) also find that the lead-lag relation between the CDS and the stock markets depends on the creditworthiness of the reference entity. Another possible reason is that the CDS spreads are not determined solely by default risk as the theory suggests but that there are also other risk factors at play (Coro et al., 2013). Further, Avramov et al. (2009) present evidence that the relation between default risk and stock returns is driven by the firms with low credit quality during turbulent time periods. However, during tranquil periods there is no clear relation between default risk and stock returns.

3. Data selection and description

We collect the daily closing midpoint spreads of the CDS indices from Thomson Reuters (TR) over the time period from January 1, 2008, to June 30, 2014.[12,13] The TR CDS indices are highly liquid benchmarks that allow investors to hedge or trade cheaper and easier sector-wide credit risk instead of using a number of single-name CDS. Our data set contains the daily closing spreads of the TR CDS indices for four geographical regions (i.e., North America, Europe, the UK, and Asia), and nine main economic sectors (i.e., Banks, Consumer Goods, Electric Power, Energy, Manufacturing, Other Financials, Service, Communications, and Transportation).[14] The CDS indices are constructed using the Dow Jones/FTSE Industry Classification Benchmark (ICB) super-sectors, and are rebalanced every six months to better reflect the liquidity in the CDS market. The CDS indices are equally weighted and reflect the average mid-spread calculation of a basket of senior unsecured single-name CDS within a given sector across the four regional subdivisions.[15] Further, we use the CDS indices for the five-year benchmark maturity tranch because they are made up of the most liquid CDS contracts and constitute the largest proportion of the CDS market (Jorion and Zhang, 2007). It should also be noted that the TR CDS indices are not made up of CDS of a particular restructuring clause. Certain restructuring clauses have become more popular in certain regions: modified restructuring in North America, modified-modified in Europe and the UK, and full restructuring in Asia.[16]

One could argue that because bonds are securities that are also sensitive to default risk, we should include bond data in our analysis. However, CDS spreads have several advantages over bond spreads. First, CDS spreads are pure measures of default risk as opposed to bond spreads that are also affected by the features of the issue such as coupon rates, seniority, embedded options, and convertibility, as well as different tax treatment (see, e.g., Elton et al., 2001). Further, Longstaff et al. (2003) find that bond spreads are determined 50–80% by liquidity factors which do not necessarily reflect default risk; however, Lin et al. (2011) report a lower liquidity premium of 20–25% for bond spreads. Second, Blanco et al. (2005), Norden and Weber (2009), and Zhu (2006) provide strong evidence that the CDS market leads the bond market in the pricing discovering process. Third, the CDS market is significantly more liquid than the bond market (Blanco et al., 2005; Schultz, 2001).

[12] The midpoint is for $10 million notional transactions of a basket of the five-year tranch of single-name CDS on senior unsecured debt. The TR CDS spreads can be actual transaction, calculated, or quoted prices, or even combinations of these.

[13] For the period from January 1, 2008, to September 30, 2010, the TR CDS indices are constructed using data on single-name CDS provided by the Credit Market Analysis (CMA). On October 1, 2010, the agreement between CMA and TR to provide CDS data was discontinued and since then, TR has relied on its proprietary data in the construction of the CDS indices.

[14] We exclude sovereign entities because it is not possible to construct the underlying stock portfolios.

[15] The seniority of the CDS contract significantly affects the CDS spreads. For the same reference entity, the spread is lower the higher the payback order and vice versa. The four different seniority orders are: junior, subordinated, senior, and preferred.

[16] The ISDA distinguishes between four different restructuring documentation clauses: full restructuring (FR), modified restructuring (MR), modified-modified (MMR) restructuring, and no restructuring (NR). A documentation clause describes what constitutes a credit event. The FR clause first appeared in the 1999 ISDA credit derivatives definitions. Under the FR clause any restructuring event qualifies as a credit event and can trigger payments. This clause is mostly preferred by the buyers of protection. The main disadvantage of this clause is that credit events that are beneficial to investors (e.g., increased bond coupons), might also trigger payments under the ISDA guidelines. In response, the ISDA introduced the MR clause in 2001. Under this clause any restructuring event still counts as a credit event but now the deliverable obligations are limited to those with a maturity of 30 months or less after the termination of the CDS. In 2003, the ISDA introduced the MMR clause in response to the perception by a part of the market that the MR clause is too restrictive in terms of deliverable obligations. The MMR clause requires deliverable obligations to be within 60 months of the termination of the CDS. Finally, under the NR clause any type of restructuring is not considered to be a credit event. Under this clause, minor credit events that do not lead to real losses to the protection buyers but might lead to opportunistic behaviour are excluded. This is the most favourable clause for sellers of protection. Packer and Zhu (2005) discuss in detail the main differences between the four different clauses and their pricing implications. They report that CDS contracts with an MR clause account for the largest part of the CDS market, and CDS contracts with an MMR clause for the smallest part of the CDS market.

We use the names and the ISIN numbers of the single-name CDS constituents of the CDS indices to match the CDS with equity. This process results in 395 North American stocks, 184 European stocks, 73 UK stocks, and 179 Asian stocks. The sectors that are represented the most are Manufacturing for North America (113), Europe (47), and Asia (86), and Other Financials for the UK (20). The daily closing prices for the stocks are obtained from TR over the time period from January 1, 2008, to June 30, 2014. This process allows us to construct the underlying stock portfolios for the CDS indices. We then calculate the daily returns of the underlying stock portfolios as an equally weighted average of the daily returns of their constituents. To be consistent with the construction of the CDS indices, we rebalance the underlying stock portfolios every six months.

Table 1 presents summary statistics for the CDS daily spreads across the different geographical regions and economic sectors. The table shows that the spreads tend to be larger and more volatile in North America and Europe compared to the UK and Asia. For example, the average spreads across the different economic sectors are 265.7 and 218.3 basis points for North America and Europe, respectively, but only 164.7 and 157.6 basis points for the UK and Asia respectively. The results for the standard deviation are similar, as well as the minimum and maximum values for the average spreads across the different economic sectors. Further, across the different regions, the higher the different sectors' default risk, the higher the standard deviation of the spreads tends to be. The results also indicate that the regions with the largest cross-sector average spreads are dominated by companies with high default risk. This is confirmed by the cross-sector average Altman's *z*-score (Altman, 1968; 1983), a measure of financial distress, that takes the high values of 2.54, 2.28, 1.97, and 1.83, for North America, Europe, the UK, and Asia respectively (Table 2).[17]

Table 2 contains the descriptive statistics for the daily percentage changes in the CDS indices' spreads and the daily returns of the underlying stock portfolios in our sample.[18] In North America, the Electric Power and Transportation sectors have larger means for the changes in the spreads with 42% and 34% respectively. These two sectors also have larger standard deviations with values of 13.64% and 9.49% respectively. All of the other sectors in this region have noticeably smaller mean spread changes and standard deviations. The Electric Power sector also has the largest mean change in its spread in Europe with a value of 38% with all of the other sectors having much lower changes in their mean spreads; this value also comes with the highest standard deviation across the European sectors.[19] In the UK, the mean spread changes are rather low in all of the sectors, with the highest value in the Bank sector. The standard deviations of the spread changes are also fairly low. Similarly, in Asia the mean changes in the spreads are also fairly low.

Table 2 also shows that the mean values of the daily stock returns are rather low in all of the regions and across the different sectors. Further, the Bank sectors in both North America and the UK are more volatile compared to all of the other sectors with a very wide range between the minimum and maximum daily returns. This finding might be because this particular sector was substantially and negatively affected in these two regions. We also calculate the pairwise correlation coefficients between the daily changes in the CDS indices' spreads and the daily returns of the underlying stock portfolios over the entire sample period. The estimated correlations indicate a fairly strong negative correlation between the changes in the CDS indices' spreads and the stock portfolios' returns across all of the different regions and economic sectors. This is consistent with theory that suggests that low stock valuations imply high CDS spreads and vice versa (i.e., Merton, 1974). It is also consistent with the more recent findings in the literature. For example, Norden and Weber (2009), Fung et al. (2008), and Byström (2008) report average correlations between the CDS and the stock markets of about −0.30, −0.34, and −0.25, respectively.

[17] The Altman's *z*-score is a measure of financial distress in which values of $z > 2.6$ indicate that a firm is in the safety zone, values between $1.1 < z < 2.6$ indicate that a firm is in the gray zone, and values of $z < 1.1$ indicate that a firm is in the bankruptcy zone. It should be noted that it is not possible to derive a meaningful Altman's *z*-score for a bank mainly because it is not possible to meaningfully calculate some of the components of the Altman's formula like the net working capital. The original Altman's *z*-score model (Altman, 1968) for publicly traded manufacturing firms is given by: $_{Z1} = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_{4A} + 0.999X_5$, where X_1 = Working Capital/Total Assets, X_2 = Retained Earnings/Total Assets, X_3 = EBIT/Total Assets, X_{4A} = Market Value Equity/Book Value of Total Debt, and X_5 = Sales/Total Assets. Altman (1983) suggests the use of the following improved model for private and publicly traded nonmanufacturing firms (US and foreign firms): $Z_3 = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_{4B,}$ where X_{4B} = Book Value Equity/Total Liabilities. In our paper we use Worldscope to collect fundamental firm data and we distinguish between manufacturing and nonmanufacturing firms. Specifically, for manufacturing firms we use the Z_1-score while for nonmanufacturing firms we use the Z_3-score. We should also note that Altman's *Z*-score model is used only as an approximate measure of financial distress for a firm and we do not rely on it to derive our main results or to draw our main inferences. The latter remain unaffected regardless of which version of the Altman's *Z*-score model we use.

[18] Hilscher et al. (2015) show that the return for a buyer of credit protection is the profit from a strategy that involves buying a CDS contract at time t_1 and selling an offsetting CDS at time t_2, divided by its implicit premium. This is because a CDS contract can be recast as an insurance agreement with an up-front premium equal to the present value of the credit spread at a particular future date *t*. Hilscher et al. (2015) show that this return is approximately equal to the percentage change in the spread, adjusted by the ratio of two annuity factors. Typically, this ratio is very close to one, which implies that the return to a CDS buyer can be accurately approximated by the percentage change in the spread. Thus, in our analysis the percentage change in the CDS spread can be thought of as a proxy for the CDS buyer's return. Further details can be found in the online appendix of Hilscher et al. (2015) at the following web address: http://people.brandeis.edu/~hilscher/HilscherPolletWilson_CDSsideshow_Appendix_Feb2013.

[19] The large mean spread changes for the Electric Power sectors might be explained by the fact that, at a global level, this sector is at a crisis mainly due to the commitment by many countries to increase energy efficiency and reduce greenhouse gas emissions. In Europe, for example, at the end of 2008 the EU adopted the *Climate and Energy Package* that implies a strong commitment to achieve a 20% reduction in EU greenhouse gas emissions from the 1990 level, produce 20% of EU energy from renewable resources, and a 20% improvement in the EU's energy efficiency (EU, 2008). However, these targets were based on rather misguided assumptions that led to an ongoing crisis in the EU energy system (CGSP, 2014).

Table 1
Descriptive statistics for the daily CDS indices' spreads.

	N	Mean	St.Dev	Min	Max
Panel A: North American	395				
Banks	5	159.3	74.0	56.2	512.1
Consumer Goods	30	154.7	43.5	83.0	345.1
Electric Power	24	273.4	118.9	83.5	663.2
Energy	44	146.7	67.7	62.9	405.8
Manufacturing	113	231.6	118.7	123.0	775.4
Other Financials	50	378.0	167.6	145.1	1099.7
Services	95	315.0	172.5	135.9	1194.6
Communications	21	245.1	100.8	107.1	621.3
Transportation	13	487.4	300.1	78.3	1393
Average		265.7	129.3	97.2	778.9
Panel B: Europe	184				
Banks	43	249.6	109.6	53.6	552.2
Consumer Goods	8	90.9	38.0	47.5	247.1
Electric Power	9	154.4	77.6	46.8	373.0
Energy	5	110.8	44.0	35.6	268.5
Manufacturing	47	256.9	143.9	102.3	796.9
Other Financials	32	271.3	130.4	87.6	780.2
Services	24	264.6	134.4	92.5	781.5
Communications	14	214.4	100.6	90.7	588.8
Transportation	2	351.8	150.0	136.5	743.6
Average		218.3	103.2	77.0	570.2
Panel C: UK	73				
Banks	10	156.0	51.1	47.5	305.5
Consumer Goods	8	85.2	31.3	53.5	231.5
Electric Power	3	137.7	78.7	52.7	425.6
Energy	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
Manufacturing	10	220.8	176.5	91.7	1029.2
Other Financials	20	206.3	159.2	84.5	940.4
Services	18	170.5	66.2	96.1	408.3
Communications	4	176.3	55.4	81.2	440.8
Transportation	N/A	N/A	N/A	N/A	N/A
Average		164.7	88.3	72.5	540.2
Panel D: Asia	179				
Banks	22	170.7	79.5	79.2	596.7
Consumer Goods	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
Electric Power	10	122.8	63.1	33.5	402.8
Energy	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*
Manufacturing	86	211.2	159.6	88.3	950.6
Other Financials	13	154.8	90.9	65.1	598.3
Services	15	189.9	115.9	38.7	823.9
Communications	12	157.3	65.6	66.3	583
Transportation	21	96.4	40	38.3	331
Average		157.6	87.8	58.5	612.3

This table displays the descriptive statistics for the CDS indices' daily spreads (i.e., midpoints between the bid and ask spreads) across the nine different economic sectors in North America, Europe, the UK, and Asia. '*N*' is the number of single-name CDS in each CDS index. The 'Mean', 'St.Dev', 'Min', and 'Max' are the daily average, standard deviation, minimum, and maximum, respectively, for the CDS spreads. 'N/A' indicates that data is not available.

4. Methodology and empirical results

4.1. The lead-lag relation between the CDS and the stock markets

The dynamics of how information related to changing default risk is absorbed by the CDS and the stock markets can be captured by the following bivariate vector autoregression (VAR) system.[20]

$$R_{CDS,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S,t-i} + \varepsilon_t \tag{1}$$

[20] Our VAR based approach has proved very popular in studies that examine the lead-lag relation between financial variables. See for example, among other, Downing et al. (2009), Ronen and Zhou (2013), Hotchkiss and Ronen (2002), Hou (2007), Tolikas (2016) , Connolly et al. (2005), Brennan et al. (1993), Hong et al. (2007), Forte and Lovreta (2015), Forte and Peña (2009), and Norden and Weber (2009).

Table 2
Descriptive statistics for the changes in the CDS indices' daily spreads and the underlying stock portfolios' daily returns.

	Stocks					CDS				
	Mean (%)	St.Dev (%)	Min (%)	Max (%)	Altman's z-score	Mean (%)	St.Dev (%)	Min (%)	Max (%)	$\rho_{s,CDS}$
Panel A: North American										
Banks	0.05	3.38	−21.25	27.76	–	0.05	4.09	−40.02	46.13	−0.377 (0.000)
Consumer Goods	0.03	1.07	−6.28	8.39	3.74	0.01	2.24	−14.81	24.98	−0.148 (0.000)
Electric Power	0.01	1.20	−7.93	13.23	0.95	0.42	13.64	−83.63	504.36	−0.038 (0.119)
Energy	0.04	1.88	−13.17	19.82	2.53	0.06	3.12	−26.01	33.77	−0.141 (0.000)
Manufacturing	0.05	1.70	−9.68	8.84	2.94	0.02	1.82	−10.85	25.34	−0.346 (0.000)
Other Financials	0.05	1.51	−8.32	11.50	1.96	0.16	5.67	−42.74	68.93	−0.144 (0.000)
Services	0.06	1.50	−8.67	9.02	2.80	0.04	2.30	−27.23	36.02	−0.256 (0.000)
Communications	0.02	1.11	−6.08	9.85	1.35	−0.01	2.32	−12.51	21.39	−0.255 (0.000)
Transportation	0.07	1.89	−10.10	8.70	2.78	0.34	9.49	−60.23	151.82	−0.074 (0.002)
Panel B: Europe										
Banks	0.00	1.88	−7.70	12.79	–	0.08	2.72	−13.83	31.23	−0.411 (0.000)
Consumer Goods	0.03	1.20	−6.74	8.80	3.17	0.03	2.27	−18.48	29.85	−0.323 (0.000)
Electric Power	−0.02	1.29	−6.80	11.63	1.13	0.38	8.82	−57.18	99.09	−0.100 (0.000)
Energy	0.02	1.67	−9.26	11.56	1.37	0.08	3.32	−24.77	33.69	−0.387 (0.000)
Manufacturing	0.03	1.76	−8.49	11.41	2.98	0.04	2.40	−15.05	22.25	−0.481 (0.000)
Other Financials	0.02	1.73	−8.87	10.66	3.38	0.05	3.74	−42.89	72.89	−0.309 (0.000)
Services	0.03	1.33	−7.82	11.83	2.04	0.04	3.71	−56.11	103.06	−0.277 (0.000)
Communications	0.00	1.21	−6.89	7.66	1.76	0.13	4.96	−38.72	65.25	−0.180 (0.000)
Transportation	−0.02	2.46	−16.70	25.48	1.30	0.05	2.89	−26.59	31.99	−0.257 (0.000)
Panel C: UK										
Banks	0.01	2.95	−27.43	28.09	–	0.13	3.96	−30.28	61.76	−0.363 (0.000)
Consumer Goods	0.02	0.89	−6.76	6.60	2.41	0.03	2.29	−14.88	25.27	−0.279 (0.000)
Electric Power	0.01	1.47	−9.87	19.38	1.07	0.01	3.75	−39.77	74.96	−0.117 (0.000)
Energy	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	
Manufacturing	0.02	1.44	−7.71	8.53	2.01	0.04	2.35	−23.37	22.06	−0.360 (0.000)
Other Financials	0.03	1.45	−8.16	9.36	2.45	0.01	2.19	−14.64	21.89	−0.393 (0.000)
Services	0.03	1.28	−6.34	10.15	2.71	0.02	2.15	−14.51	16.95	−0.354 (0.000)
Communications	0.04	1.57	−9.21	16.03	1.35	0.03	3.44	−36.04	101.40	−0.241 (0.000)
Transportation	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	
Panel D: Asia										
Banks	0.02	1.27	−6.71	7.24	–	0.07	3.26	−18.38	29.82	−0.367 (0.000)
Consumer Goods	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	
Electric Power	0.00	1.18	−9.13	7.03	0.91	0.14	4.14	−27.85	44.39	−0.163 (0.000)
Energy	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	
Manufacturing	0.03	1.76	−10.81	13.89	2.24	0.01	2.45	−22.95	24.53	−0.373 (0.000)
Other Financials	0.03	1.42	−7.84	9.26	2.52	0.07	3.06	−21.65	32.36	−0.398 (0.000)
Services	0.01	1.67	−11.00	13.28	1.82	0.21	5.41	−46.48	86.02	−0.090 (0.000)
Communications	0.03	1.04	−8.60	5.40	2.22	0.14	4.74	−28.92	86.07	−0.253 (0.000)
Transportation	0.01	1.14	−9.23	9.59	1.26	0.09	3.79	−19.53	46.11	−0.312 (0.000)

This table displays the descriptive statistics for the changes in the CDS indices' daily spreads and the underlying stock portfolios' daily returns for the nine economic sectors and the four geographical regions we examine over the period from January 1, 2008 to June 30, 2014. The 'Mean', 'St.Dev', 'Min', and 'Max' are the daily average, standard deviation, minimum, and maximum values, respectively, for the changes in the CDS indices' spreads and the underlying stock portfolios' returns. The '$\rho_{s,CDS}$' is the correlation coefficient between the changes in the daily spreads and the returns (the p-value of the null hypothesis that the estimated correlation coefficient is statistically equal to zero is given in parenthesis). The 'Altman's z-score' gives the Altman's (1983) average measure of financial distress ($z > 2.6$ indicates that a firm is in the *safety* zone, $1.1 < z < 2.6$ indicates that a firm is in the *gray* zone, and $z < 1.1$ indicates that a firm is in the *bankruptcy* zone). A ' – ' indicates that the calculation of Altman's z-score is not meaningful for the Bank sector. This is because it is not possible to meaningfully calculate the net working capital of a bank. 'N/A' indicates that data is not available.

$$R_{S,t} = a + \sum_{i=1}^{L} \beta_i R_{CDS,t-i} + \sum_{i=1}^{L} \gamma_i R_{S,t-i} + \varepsilon_t$$

where $R_{CDS,t}$ is the daily change in the spread of the TR CDS index at time t, $R_{S,t}$ is the daily return of the underlying stock portfolio at time t, and L is the lag length. The α is the intercept term, β_i and γ_i are the cross-market coefficients to be estimated respectively, and ε_t is the error term that follows a multivariate normal distribution with known variance that is only correlated contemporaneously. As noted by Longstaff et al. (2003), by including the lagged terms we minimize the risk of obtaining a spurious relation due to stale quotes or infrequent updates of prices. We determine the optimal length of the lags by using the Schwarz's (1978) Bayesian information criterion (SIC) that chooses the number of lags that minimizes the value of the information criterion.[21] In most cases, the SIC indicates a maximum lag length of order 3 for the daily changes

[21] The Schwarz Bayesian information criterion is considered to be the strictest information criterion compared to the Akaike and the Hannan-Quinn information criteria. The SIC penalizes the loss of a degree of freedom resulting from including more estimated parameters in the fitted model.

in the CDS spreads and stock returns; and therefore the order of the lags in the bivariate VAR system is set to equal three.[22] The two dependent CDS and stock market attributes, $R_{CDS,t}$ and $R_{S,t}$, need to be stationary processes. We test for stationarity in the daily changes of the indices' spreads and the daily returns of the underlying stock portfolios using the augmented Dickey-Fuller and the Phillips-Perron tests (Dickey and Fuller, 1979; Phillips and Perron, 1988). The null hypothesis of nonstationarity is rejected by both tests for all of the time series at the 5% significance level. Further, we use the Johansen's cointegration test (Johansen, 1991) to test for cointegration between the two markets. We find that the two markets are not cointegrated for the sample period. Therefore, we use the VAR system instead of a vector error correction model (VECM) in our analysis.

The null hypothesis is that the CDS and the stock markets in each geographical region and economic sector are equally efficient in processing information. This null implies that the information about changing default risk is simultaneously embedded in the two markets. If this is the case, then the estimated coefficients of all of the cross-market lagged terms should be statistically equal to zero. To test the null hypothesis that the CDS spread changes do not lead the stock returns, we examine the Granger (1969) causality test statistic that is the *F*-statistic of the hypothesis that $H_0 = [\beta_i] = 0$ for all *i*. To test the null hypothesis that the stock returns do not lead the CDS spread changes, we examine the *F*-statistic of the hypothesis that $H_0 = [\gamma_i] = 0$ for all *i*. We use ordinary least squares to estimate the VAR system and report the results for North America, Europe, the UK, and Asia in Tables 3–6 respectively.

The results in Table 3 show that the lagged stock returns have predictive power for the changes in the CDS spreads.[23] Specifically, with the exemption of the Electric Power sector, there are many statistically significant coefficients for the lagged stock returns that help to explain the changes in the CDS spreads in all of the other sectors. For example, for the Banks sector the coefficients of the first two lagged stock returns take the values of −0.233 and −0.122, and are highly statistically significant with *t*-statistics of −7.479 and −3.827, respectively. The null hypothesis that lagged stock returns do not Granger-cause changes in the CDS spreads is also strongly rejected with an *F*-statistic of 11.544. On the other hand, the lagged changes in the CDS spreads have modest predictive power for the stock returns in the Banks, Consumer Goods, Energy, Other Financials, Services, and Communications sectors. For example, for the Consumer Goods sector, it is only the coefficient of the lagged of order three CDS spread changes that is statistically significant at the 5% level with an estimated value of 0.021. The Granger test rejects the null hypothesis that the lagged stock returns do not affect the changes in the CDS spreads in all but the Electric Power sector; in this case the Granger *F*-statistic takes the value of 0.279 with a *p*-value of 0.841. Further, the Granger test rejects the null hypothesis that the lagged changes in the CDS spreads do not affect the stock returns in the Banks, Energy, Services, and Communications sectors. In general, our results provide strong evidence that the stock market in North America reacts faster to changes in default risk than the CDS market and therefore leads the price discovery process. It should also be noted that, unsurprisingly, the lagged stock returns clearly have a negative impact on the changes in the CDS spreads that become weaker at higher lags (also found by Norden and Weber, 2009).[24] The results in Table 4 on the European region further support this finding. In particular, the statistically significant estimated coefficients for the lagged stock returns strongly indicate that the stock market leads the CDS market in all of the sectors. For example, in the case of the Consumer Goods sector, the estimated coefficients for the lagged stock returns of order one and two are −0.298 and −0.135 with highly statistically significant *t*-statistics of −6.130 and −2.763, respectively. This effect is asymmetric given that the VAR system picks up statistically significant coefficients for the lagged changes in the CDS spreads only in the Banks, Consumer Goods, Other Financials, and Communications sectors. In all of the sectors, the Granger test rejects the null hypothesis that the lagged stock returns do not affect the changes in the CDS spreads. However, for the case of the lagged changes in the CDS spreads, this is true only in the Banks, Consumer Goods, Other Financials, and Communications sectors, where the *F*-statistic of the Granger test takes *p*-values ranging from 0.000 to 0.009. Thus, we conclude that the stock market leads the price discovery process in relation to the CDS market. The results in Table 5 for the UK lead to similar conclusions. In particular, the lagged stock returns have predictive power for the changes in the CDS spreads in all of the economic sectors, but the lagged changes in the CDS spreads affect the stock returns in the Banks, Consumer Goods, Manufacturing, and Other Financials sectors. The Granger test rejects the null hypothesis that the lagged stock returns do not affect the changes in the CDS spreads in all of the sectors. But for the lagged changes in the CDS spreads, this is

[22] Our choice of the number of lags is also confirmed by the Hannan-Quinn information criterion (Hannan and Quinn, 1979). The indications about the appropriate lag length provided by the Akaike criterion are much more volatile. In principle, examining predictability of CDS spread changes by equity returns (and vice versa) for a high number of lags doesn't make a lot of economic sense because, in the absence of limits to arbitrage, predictability at longer horizons should be highly unlikely. This is empirically confirmed by the optimal umber of lags we use in our study, which are determined by the Schwarz Bayesian information criterion. This is also confirmed by the maximum number of lags used by past literature which is of the same magnitude to the number of lags we identify as appropriate. For example, Forte and Peña (2009) assumes predictability between CDS and stock returns at 1, 2 and 3 lags, determined according to the Schwarz criterion. Marsh and Wagner (2015) use the Akaike information criterion and choose a lag length of 1 day in most cases. They also report that their results are not sensitive to the choice of the lag length. Hilscher et al. (2015) examine predictability of CDS returns by equity returns using time lags of 4 and 5 trading days. Norden and Weber (2009) choose a maximum lag of order 5 for daily data, and 2 for monthly and weekly data, on the basis of the Akaike information criterion. Acharya and Johnson (2007) assume a daily lag of order 5.

[23] The estimates for the intercept term, α, are statistically equal to zero in all of the geographical regions and economic sectors. This is because the CDSs are pure measures of default risk without a component for the interest rate risk. Thus, the estimates of the intercept terms are not reported in Tables 3–6.

[24] This negative relation comes as no surprise. Information about an increase in the future value of a firm's assets leads to its stock price's increase and signals a decrease in the firm's probability of default on its debt. Therefore, the spread of the firm's CDS should decrease. Hence, a negative relation between the stock returns and the changes in the CDS spread should be observed. Further, information that relates to increasing stock price volatility, increases the stock return but can also lead to a higher CDS spread because the default risk increases too. Thus, a negative relation should be observed between the stock returns and the changes in the CDS spread changes. Alexander and Kaeck (2008) find that spread changes in the CDS iTraxx Europe indices are very sensitive to stock market volatility during periods of turbulence in the CDS market and more sensitive to stock returns than stock volatility during ordinary periods.

Table 3
The relation between the changes in the CDS indices' daily spread and underlying stock portfolios' returns: North America.

	Lagged CDS spread changes			Lagged stock returns				
	β_1	β_2	β_3	γ_1	γ_2	γ_3	*N*	Granger
Banks							1692	
CDS	0.115 (4.308**)	−0.014 (−0.516)	−0.065 (−2.534**)	−0.233 (−7.479**)	−0.122 (−3.827**)	−0.016 (−0.500)		11.544 (0.000)
Stock	0.015 (0.648)	−0.025 (−1.096)	0.126 (5.859**)	−0.061 (−2.302*)	0.030 (1.109)	−0.038 (−1.1446)		21.308 (0.000)
Consumer Goods							1692	
CDS	−0.076 (−3.069**)	0.051 (2.071*)	0.020 (0.842)	−0.301 (−5.905**)	−0.217 (−4.217**)	−0.145 (−2.819**)		9.007 (0.000)
Stock	−0.004 (−0.307)	−0.001 (−0.069)	0.021 (1.818*)	−0.096 (−3.870**)	−0.080 (−3.203**)	0.035 (1.413)		1.111 (0.343)
Electric Power							1692	
CDS	−0.018 (−0.740)	−0.002 (−0.101)	−0.038 (−1.557)	−0.001 (−0.002)	−0.202 (−0.717)	−0.079 (−0.284)		0.279 (0.841)
Stock	−0.001 (−0.528)	−0.001 (−0.415)	−0.001 (−0.636)	−0.119 (−4.867**)	−0.060 (−2.448**)	0.040 (1.659*)		0.188 (0.905)
Energy							1692	
CDS	−0.150 (−6.183**)	−0.053 (−2.170*)	0.144 (6.020**)	−0.275 (−6.978**)	−0.174 (−4.365**)	−0.118 (−2.949**)		2.798 (0.039)
Stock	0.009 (0.583)	0.020 (1.320)	0.040 (2.715**)	−0.047 (−1.920**)	−0.069 (−2.788**)	0.048 (1.939**)		22.592 (0.000)
Manufacturing							1692	
CDS	0.108 (4.111**)	0.101 (3.869**)	0.037 (1.483)	−0.281 (−10.794**)	−0.067 (−2.466**)	−0.043 (−1.607)		3.259 (0.021)
Stock	0.018 (0.671)	0.005 (0.178)	0.026 (1.060)	0.001 (0.044)	0.016 (0.574)	−0.002 (−0.063)		2.133 (0.094)
Other Financials							1692	
CDS	−0.329 (−13.373**)	−0.220 (−8.691**)	−0.057 (−2.337**)	−0.576 (−6.633**)	−0.307 (−3.494**)	−0.173 (−1.965*)		2.899 (0.034)
Stock	−0.001 (−0.099)	−0.001 (−0.180)	0.012 (1.777*)	0.013 (0.537)	0.016 (0.647)	−0.001 (−0.040)		1.713 (0.162)
Services							1692	
CDS	−0.079 (−3.131**)	0.064 (2.601**)	0.014 (0.571)	−0.345 (−9.304**)	−0.228 (−5.994**)	−0.151 (3.934**)		2.834 (0.037)
Stock	−0.030 (−1.733*)	−0.041 (−2.443**)	0.005 (0.330)	−0.004 (−0.157)	−0.035 (−1.341)	−0.024 (−0.935)		41.454 (0.000)
Communications							1692	
CDS	−0.065 (−2.615**)	0.070 (2.823**)	0.040 (1.655*)	−0.471 (−9.275**)	−0.090 (−1.730*)	−0.276 (−5.331**)		9.546 (0.000)
Stock	0.007 (0.608)	−0.049 (−4.015**)	0.040 (3.274**)	0.010 (0.393)	−0.090 (−3.535**)	−0.019 (−0.759)		35.842 (0.000)
Transportation							1692	
CDS	−0.230 (−9.420**)	−0.159 (−6.447**)	−0.046 (−1.884*)	−0.204 (−1.722*)	−0.150 (−1.264)	−0.237 (−2.000*)		4.684 (0.003)
Stock	0.006 (1.253)	0.007 (1.464)	0.007 (1.332)	−0.026 (−1.081)	−0.017 (−0.682)	−0.010 (−0.391)		2.529 (0.056)

This table presents the estimates of the following bivariate vector autoregressive model:
$R_{CDS,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S,t-i} + \varepsilon_t$
$R_{S,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S,t-i} + \varepsilon_t$
where $R_{CDS,t}$ is the changes in the daily spread of the Thomson Reuters CDS index at time t, $R_{S,t}$ is the daily return of the underlying stock portfolio at time t, and L (= 3) is the lag length. The α is the intercept term, β_i and γ_i are the coefficients to be estimated respectively, and ε_t is the error term. The t-statistics of the coefficient estimates are given in parentheses below the estimates. '*', and '**' denote statistical significance at the 5% and 1% level respectively. The '*N*' is the number of data points, and 'Granger' is the F-statistic (p-value in parenthesis) of the null hypothesis that all estimated coefficients are statistically equal to zero.

true only for the Banks, Consumer Goods, and Manufacturing sectors. In particular, the Granger test takes the F-statistic values of 5.663, 3.500, and 3.293 which lead to p-values very close to zero. The results are similar in Table 6 for the Asian region. The lagged stock returns lead the changes in the CDS spreads in all of the sectors. But for the lagged changes in the CDS spreads, this is true for the Banks, Electric Power, Other Financials, and Communications sectors. Overall, the results indicate that, across all regions, the returns of the stock portfolios lead the changes in the CDS spreads in all of the economic sectors. Although the results also indicate that the lagged changes in the CDS spreads lead the stock returns, the estimated coefficients are of a much smaller magnitude.

Table 4
The relation between the changes in the CDS indices' daily spreads and underlying stock portfolios' returns: Europe.

	Lagged CDS spread changes			Lagged Stock returns				
	β_1	β_2	β_3	γ_1	γ_2	γ_3	N	Granger
Banks							1692	
CDS	−0.033 (−1.236)	0.015 (0.552)	−0.037 (−1.423)	−0.307 (−8.117**)	−0.039 (−1.020)	−0.093 (−2.408**)		23.702 (0.000)
Stock	−0.043 (−2.306**)	0.003 (0.144)	0.051(2.790**)	0.066 (2.502**)	−0.021 (−0.780)	−0.022 (−0.802)		4.246 (0.005)
Consumer Goods							1692	
CDS	−0.006 (−0.236)	−0.002 (−0.085)	0.014 (0.539)	−0.298 (−6.130**)	−0.135 (−2.763**)	−0.037 (−0.755)		14.156 (0.000)
Stock	−0.007 (−0.540)	−0.047 (−3.452**)	0.021 (1.562)	−0.046 (−1.785*)	−0.110 (−4.251**)	−0.069 (−2.656**)		4.851 (0.002)
Electric Power							1692	
CDS	−0.080 (−3.284**)	−0.064 (−2.634**)	−0.077 (−3.150**)	−0.429 (−2.568**)	−0.184 (−1.103)	0.107 (0.641)		2.922 (0.033)
Stock	0.001 (0.384)	−0.006 (−1.582)	0.005 (1.317)	0.065 (2.648**)	−0.075 (−3.051**)	−0.005 (−0.208)		1.582 (0.192)
Energy							1692	
CDS	0.162 (6.119**)	0.007 (0.245)	0.012 (0.442)	−0.177 (−3.417**)	0.108 (2.073*)	0.104 (2.001*)		7.198 (0.000)
Stock	−0.008 (−0.614)	−0.020 (−1.428)	0.022 (1.628)	−0.036 (−1.351)	−0.105 (−3.951**)	−0.043 (−1.627)		1.584 (0.192)
Manufacturing							1692	
CDS	0.041 (1.464)	0.080 (2.874**)	0.044 (1.633)	−0.362 (−9.931**)	−0.015 (−0.390)	−0.057 (−1.540)		33.585 (0.000)
Stock	0.007 (0.310)	0.007 (0.331)	0.027 (1.320)	0.075 (2.682**)	−0.019 (−0.651)	−0.047 (−1.659*)		0.733 (0.532)
Other Financials							1692	
CDS	−0.269 (−10.505**)	−0.024 (−0.930)	−0.015 (−0.588)	−0.495 (−9.348**)	−0.231 (−4.276**)	−0.077 (−1.420)		35.405 (0.000)
Stock	0.015 (1.221)	−0.018 (−1.455)	0.026 (2.159**)	0.073 (2.852**)	−0.043 (−1.642)	−0.045 (−1.708*)		3.868 (0.009)
Services							1692	
CDS	0.001 (0.052)	0.028 (1.119)	−0.001 (−0.031)	−0.475 (−6.805**)	−0.016 (−0.223)	−0.089 (−1.258)		15.851 (0.000)
Stock	0.012 (1.338)	−0.015 (−1.674*)	0.002 (0.240)	0.086 (3.399**)	−0.039 (−1.520)	−0.049 (−1.903*)		1.534 (0.204)
Communications							1692	
CDS	−0.320 (−12.890**)	−0.228 (−8.986**)	−0.026 (−1.085)	−0.965 (−10.153**)	−0.455 (−4.685**)	−0.199 (−2.036*)		40.576 (0.000)
Stock	−0.004 (−0.623)	−0.018 (−2.696**)	0.000 (−0.044)	−0.001 (−0.054)	−0.074 (−2.916**)	−0.074 (−2.894**)		2.641 (0.048)
Transportation							1692	
CDS	0.008 (0.309)	0.049 (1.952*)	−0.012 (−0.492)	−0.217 (−7.535**)	−0.090 (−3.071**)	−0.080 (−2.734**)		23.823 (0.000)
Stock	0.009 (0.392)	−0.018 (−0.803)	0.020 (0.950)	0.011 (0.432)	0.021 (0.808)	−0.025 (−0.982)		0.562 (0.640)

This table presents the estimates of the following bivariate vector autoregressive model:

$R_{CDS,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S,t-i} + \varepsilon_t$

$R_{S,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S,t-i} + \varepsilon_t$

where $R_{CDS,t}$ is the changes in the daily spread of the Thomson Reuters CDS index at time t, $R_{S,t}$ is the daily return of the underlying stock portfolio at time t, and L (= 3) is the lag length. The α is the intercept term, β_i and γ_i are the coefficients to be estimated respectively, and ε_t is the error term. The t-statistics of the coefficient estimates are given in parentheses below the estimates. '*', and '**' denote statistical significance at the 5% and 1% level respectively. The 'N' is the number of data points, and 'Granger' is the F-statistic (p-value in parenthesis) of the null hypothesis that all estimated coefficients are statistically equal to zero.

We provide further insights into the relation between the stock and CDS markets by computing the accumulated impulse responses of the CDS sectoral indices, and the underlying stock portfolios returns for the North America, Europe, Asia, and UK regions, to a one standard deviation shock to each other and their lagged values. The impulse responses capture the dynamic properties of the relation between the two markets by providing an insight on how the CDS and the stock markets respond to shocks to the variables in the VAR system. Table 7 show the accumulated impulse responses between the changes in the CDS indice spreads and the underlying stock portfolio returns for up to 10 lags. The results show that in most cases the accumulated responses of the CDS indices to a one standard deviation shock in the returns of the underlying stock portfolios are

Table 5
The relation between the changes in the CDS indices' daily spreads and underlying stock portfolios' returns: UK.

	Lagged CDS spread changes			Lagged Stock returns				
	β_1	β_2	β_3	γ_1	γ_2	γ_3	N	Granger
Banks							1692	
CDS	0.111 (4.248**)	0.025 (0.948)	−0.053 (−2.055*)	−0.179 (−5.196**)	0.056 (1.606)	−0.083 (−2.402**)		11.908 (0.000)
Stock	0.007 (0.377)	0.016 (0.787)	0.076 (3.881**)	0.049 (1.897*)	0.000 (−0.016)	0.046 (1.772*)		5.663 (0.001)
Consumer Goods							1692	
CDS	0.016 (0.611)	−0.013 (−0.499)	0.057 (2.278*)	−0.368 (−5.633**)	−0.066 (−1.001)	0.015 (0.233)		10.869 (0.000)
Stock	−0.011 (−1.163)	0.027 (2.733**)	0.012 (1.280)	−0.037 (−1.440)	−0.072 (−2.819**)	−0.066 (−2.580**)		3.500 (0.015)
Electric Power							1692	
CDS	−0.221 (−9.050**)	0.016 (0.651)	−0.076 (−3.101**)	−0.308 (−5.026**)	−0.054 (−0.880)	−0.083 (−1.343)		8.674 (0.000)
Stock	0.015 (1.536)	0.010 (0.995)	0.000 (−0.026)	−0.039 (−1.578)	−0.153 (−6.294**)	−0.070 (−2.860**)		0.947 (0.417)
Energy								
CDS	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*		*N/A*
Stock	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*		*N/A*
Manufacturing							1692	
CDS	0.091 (3.475**)	0.076 (2.918**)	0.040 (1.555)	−0.265 (−6.395**)	−0.044 (−1.055)	−0.021 (−0.497)		14.049 (0.000)
Stock	−0.008 (−0.470)	−0.038 (−2.296*)	0.037 (2.330**)	0.064 (2.446**)	−0.088 (−3.359**)	−0.042 (−1.597)		3.293 (0.020)
Other Financials							1692	
CDS	0.028 (1.057)	0.032 (1.224)	0.037 (1.413)	−0.245 (−6.194**)	−0.012 (−0.292)	−0.090 (−2.248*)		13.842 (0.000)
Stock	−0.011 (−0.622)	−0.012 (−0.686)	0.046 (2.655**)	0.023 (0.856)	−0.081 (−3.040**)	−0.034 (−1.280)		2.551 (0.054)
Services							1692	
CDS	−0.030 (−1.168)	−0.033 (−1.288)	0.091 (3.622**)	−0.357 (−8.422**)	−0.116 (−2.696**)	−0.058 (−1.354)		26.124 (0.000)
Stock	0.017 (1.045)	−0.009 (−0.582)	0.036 (1.614)	0.062 (2.373**)	−0.054 (−2.064*)	−0.066 (−2.510**)		1.406 (0.239)
Communications							1692	
CDS	−0.159 (−6.312**)	0.007 (0.264)	0.026 (1.056)	−0.242 (−4.442**)	−0.115 (−2.109*)	−0.024 (−0.440)		7.767 (0.000)
Stock	0.002 (0.181)	−0.011 (−0.980)	0.002 (0.142)	−0.030 (−1.187)	−0.091 (−3.621**)	−0.062 (−2.461**)		0.387 (0.762)
Transportation								
CDS	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*		*N/A*
Stock	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*		*N/A*

This table presents the estimates of the following bivariate vector autoregressive model:
$R_{CDS,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S,t-i} + \varepsilon_t$
$R_{S,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S,t-i} + \varepsilon_t$
where $R_{CDS,t}$ is the changes in the daily spread of the Thomson Reuters CDS index at time t, $R_{S,t}$ is the daily return of the underlying stock portfolio at time t, and L (= 3) is the lag length. The α is the intercept term, β_i and γ_i are the coefficients to be estimated respectively, and ε_t is the error term. The t-statistics of the coefficient estimates are given in parentheses below the estimates. '*', and '**' denote statistical significance at the 5% and 1% level respectively. The '*N*' is the number of data points, and 'Granger' is the F-statistic (p-value in parenthesis) of the null hypothesis that all estimated coefficients are statistically equal to zero. '*N/A*' indicates that data is not available.

always higher than those of the underlying stock portfolios to a one standard deviation shock in the returns of the CDS indices. For example, the accumulated responses of the CDS index for the Asian Banks to a one standard deviation shock in the returns of the underlying stock portfolios is 3.88% as opposed to 1.14% for their stock portfolio counterpart. These results indicate that the impact of stock returns to CDS spread changes is greater than the other way around, which provides further support to the results obtained from the Granger test.

4.2. Regime dependence and assymetric response to positive and negative news

For robustness, we also reproduce our results for the weekly spread changes of an equally-weighted portfolio of the CDS indices and the underlying stock portfolio over the whole time period, as well as for two sub-periods that cover the credit crisis period, January 01, 2008, to March 03, 2011, and the after credit crisis period, April 01, 2011, to June 30, 2014. The

Table 6
The relation between the changes in the CDS indices' daily spreads and underlying stock portfolios' returns: Asi**a.**

	Lagged CDS spread changes			Lagged Stock returns				
	β_1	β_2	β_3	γ_1	γ_2	γ_3	*N*	Granger
Banks							1692	
CDS	−0.085 (−3.270**)	0.015 (0.562)	0.046 (1.784*)	−0.528 (−8.036**)	−0.110 (−1.641)	−0.079 (−1.180)		2.898 (0.034)
Stock	−0.023 (−2.214*)	−0.022 (−2.105*)	0.003 (0.290)	0.053 (2.036*)	−0.030 (−1.131)	−0.042 (−1.568)		22.440 (0.000)
Consumer Goods							1692	
CDS	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*		*N/A*
Stock	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*		*N/A*
Electric Power							1692	
CDS	0.041 (1.660*)	0.018 (0.732)	0.018 (0.729)	−0.328 (−3.806**)	−0.035 (−0.404)	−0.014 (−0.159)		6.358 (0.000)
Stock	−0.008 (−1.091)	−0.020 (−2.776**)	0.023 (3.264**)	0.004 (0.154)	−0.012 (−0.499)	0.032 (1.280)		4.870 (0.002)
Energy								
CDS	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*		*N/A*
Stock	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*	*N/A*		*N/A*
Manufacturing							1692	
CDS	−0.037 (−1.408)	0.162 (6.274**)	0.034 (1.307)	−0.223 (−6.251**)	0.032 (0.898)	−0.052 (−1.448)		1.418 (0.236)
Stock	−0.028 (−1.475)	−0.027 (−1.400)	0.014 (0.707)	0.030 (1.139)	−0.050 (−1.904*)	−0.051 (−1.920*)		13.893 (0.000)
Other Financials							1692	
CDS	−0.051 (1.929*)	0.101 (3.805**)	0.006 (0.226)	−0.320 (−5.666**)	0.058 (1.021)	−0.127 (−2.243*)		3.087 (0.026)
Stock	−0.036 (−2.927**)	−0.013 (−1.064)	0.003 (0.258)	0.057 (2.159*)	0.018 (0.660)	−0.061 (−2.282*)		12.956 (0.000)
Services							1692	
CDS	−0.122 (−5.047**)	−0.171 (−7.139**)	−0.164 (−6.815**)	−0.245 (−3.186**)	−0.142 (−1.840*)	−0.172 (−2.229*)		0.148 (0.931)
Stock	0.000 (0.050)	−0.001 (−0.134)	0.005 (0.635)	0.006 (0.240)	−0.027 (−1.087)	−0.027 (−1.096)		6.021 (0.000)
Communications							1692	
CDS	−0.059 (−2.339**)	−0.052 (−2.072*)	0.018 (0.731)	−0.454 (−3.961**)	0.038 (0.334)	0.046 (0.405)		9.233 (0.000)
Stock	−0.016 (−2.942**)	−0.021 (−3.738**)	−0.017 (−3.070**)	0.009 (0.373)	0.015 (0.578)	−0.059 (−2.349**)		5.311 (0.001)
Transportation							1692	
CDS	−0.054 (−2.095*)	0.037 (1.457)	0.078 (3.051**)	−0.281 (−3.321**)	0.167 (1.964*)	−0.006 (−0.075)		0.912 (0.434)
Stock	−0.006 (−0.769)	−0.008 (−1.042)	0.008 (1.027)	−0.020 (−0.788)	−0.055 (−2.130*)	−0.045 (−1.757*)		5.167 (0.002)

This table presents the estimates of the following bivariate vector autoregressive model:

$R_{CDS,t} = a + \sum_{i=1}^{L} \beta_i R_{CDS,t-i} + \sum_{i=1}^{L} \gamma_i R_{S,t-i} + \varepsilon_t$

$R_{S,t} = a + \sum_{i=1}^{L} \beta_i R_{CDS,t-i} + \sum_{i=1}^{L} \gamma_i R_{S,t-i} + \varepsilon_t$

where $R_{CDS,t}$ is the changes in the daily spread of the Thomson Reuters CDS index at time t, $R_{S,t}$ is the daily return of the underlying stock portfolio at time t, and L (= 3) is the lag length. The α is the intercept term, β_i and γ_i are the coefficients to be estimated respectively, and ε_t is the error term. The t-statistics of the coefficient estimates are given in parentheses below the estimates. '*', and '**' denote statistical significance at the 5% and 1% level respectively. The '*N*' is the number of data points, and 'Granger' is the F-statistic (p-value in parenthesis) of the null hypothesis that all estimated coefficients are statistically equal to zero. '*N/A*' indicates that data is not available.

results for both the whole time period and the two sub-periods are provided in Tables 8–11 and further support our findings. For example, in the North America region, the coefficient estimates for the lagged stock returns are all strongly statistically significant with values of −0.325, −0.154, and −0.099 and t-statistics of −7.861, −3.653, and −2.375, respectively. Further, the F-statistic rejects the hypothesis that stock returns do not lead the CDS spread changes with a value of 5.308 and a p-value of 0.001.Similar are the findings for all other regions. Our results also indicate that our findings are not regime-dependant but that they likely reflect a more general relation between the stock and the CDS markets. For example, in the UK, the F-statistics for the credit crisis period and the after credit crisis period reject the hypothesis that stock returns do not lead the CDS spread changes with values of 1.539 and 2.001, respectively. On the other hand, the F-statistics for the credit crisis period and the after credit crisis period do not reject the hypothesis that CDS spread changes do not lead the stock returns with values of 7.866 and 5.886, respectively. Similar are our findings for the other regions.

Table 7
Impulse responses to a one standard deviation shock for up to 10 lags.

Region	Response period	North America		Europe		UK		Asia	
		CDS response to Stocks	Stocks response to CDS	CDS response to Stocks	Stocks response to CDS	CDS response to Stocks	Stocks response to CDS	CDS response to Stocks	Stocks response to CDS
Banks									
	t + 1	3.92%	3.03%	2.66%	1.70%	3.87%	2.73%	3.18%	1.18%
	t + 2	4.65%	2.87%	2.81%	1.82%	4.47%	2.88%	3.13%	1.23%
	t + 3	4.78%	2.92%	2.91%	1.81%	4.57%	2.88%	3.26%	1.21%
	t + 4	4.56%	2.83%	2.88%	1.77%	4.47%	3.00%	3.41%	1.16%
	t + 5	4.22%	2.82%	2.92%	1.82%	4.30%	3.13%	3.56%	1.12%
	t + 6	3.93%	2.56%	2.90%	1.71%	4.11%	2.96%	3.75%	1.08%
	t + 7	3.83%	2.58%	2.89%	1.69%	4.01%	2.93%	3.79%	1.10%
	t + 8	3.81%	2.54%	2.88%	1.69%	4.00%	2.93%	3.81%	1.12%
	t + 9	3.86%	2.56%	2.88%	1.70%	4.01%	2.92%	3.85%	1.13%
	t + 10	3.91%	2.57%	2.88%	1.69%	4.04%	2.90%	3.88%	1.14%
Consumer Goods									
	t + 1	2.19%	1.05%	2.24%	1.11%	2.25%	0.84%	*N/A*	*N/A*
	t + 2	2.05%	0.95%	2.34%	1.07%	2.37%	0.81%	*N/A*	*N/A*
	t + 3	2.19%	0.88%	2.38%	0.97%	2.36%	0.77%	*N/A*	*N/A*
	t + 4	2.20%	0.94%	2.42%	0.92%	2.44%	0.71%	*N/A*	*N/A*
	t + 5	2.14%	0.95%	2.42%	1.04%	2.42%	0.78%	*N/A*	*N/A*
	t + 6	2.12%	0.92%	2.55%	0.97%	2.48%	0.77%	*N/A*	*N/A*
	t + 7	2.11%	0.93%	2.55%	0.96%	2.49%	0.77%	*N/A*	*N/A*
	t + 8	2.11%	0.93%	2.55%	0.97%	2.46%	0.76%	*N/A*	*N/A*
	t + 9	2.11%	0.93%	2.54%	0.98%	2.45%	0.76%	*N/A*	*N/A*
	t + 10	2.12%	0.93%	2.54%	0.97%	2.46%	0.76%	*N/A*	*N/A*
Electric Power									
	t + 1	13.56%	1.19%	8.73%	1.28%	3.62%	1.43%	4.12%	1.16%
	t + 2	13.24%	1.05%	8.06%	1.36%	2.85%	1.39%	4.37%	1.15%
	t + 3	13.21%	0.99%	7.58%	1.27%	3.06%	1.17%	4.47%	1.14%
	t + 4	12.67%	1.06%	6.97%	1.25%	2.72%	1.07%	4.60%	1.19%
	t + 5	10.89%	1.08%	6.42%	1.27%	2.97%	1.20%	4.36%	1.21%
	t + 6	10.91%	1.07%	6.99%	1.21%	2.99%	1.17%	4.55%	1.23%
	t + 7	10.95%	1.07%	7.01%	1.20%	2.98%	1.14%	4.54%	1.22%
	t + 8	11.09%	1.07%	7.05%	1.21%	2.95%	1.14%	4.54%	1.22%
	t + 9	11.33%	1.07%	7.02%	1.21%	2.95%	1.15%	4.57%	1.23%
	t + 10	11.33%	1.07%	6.95%	1.21%	2.96%	1.15%	4.55%	1.23%
Energy									
	t + 1	2.99%	1.85%	3.23%	1.51%	*N/A*	*N/A*	*N/A*	*N/A*
	t + 2	2.59%	1.77%	3.86%	1.46%	*N/A*	*N/A*	*N/A*	*N/A*
	t + 3	2.48%	1.64%	3.93%	1.30%	*N/A*	*N/A*	*N/A*	*N/A*
	t + 4	2.91%	1.72%	3.91%	1.25%	*N/A*	*N/A*	*N/A*	*N/A*
	t + 5	2.79%	1.70%	3.88%	1.29%	*N/A*	*N/A*	*N/A*	*N/A*
	t + 6	2.85%	1.62%	4.11%	1.22%	*N/A*	*N/A*	*N/A*	*N/A*
	t + 7	2.87%	1.61%	4.16%	1.22%	*N/A*	*N/A*	*N/A*	*N/A*
	t + 8	2.81%	1.61%	4.17%	1.24%	*N/A*	*N/A*	*N/A*	*N/A*
	t + 9	2.83%	1.60%	4.17%	1.24%	*N/A*	*N/A*	*N/A*	*N/A*
	t + 10	2.83%	1.60%	4.16%	1.23%	*N/A*	*N/A*	*N/A*	*N/A*
Manufacturing									
	t + 1	1.68%	1.57%	2.28%	1.51%	2.27%	1.33%	2.39%	1.62%
	t + 2	2.01%	1.58%	2.68%	1.63%	2.59%	1.42%	2.43%	1.68%
	t + 3	2.22%	1.59%	2.89%	1.59%	2.81%	1.32%	2.79%	1.61%
	t + 4	2.29%	1.59%	3.04%	1.51%	2.92%	1.25%	2.86%	1.53%
	t + 5	2.41%	1.54%	3.05%	1.57%	2.97%	1.33%	3.02%	1.49%
	t + 6	2.47%	1.49%	3.17%	1.51%	3.11%	1.29%	3.16%	1.58%
	t + 7	2.47%	1.49%	3.16%	1.49%	3.14%	1.28%	3.18%	1.58%
	t + 8	2.47%	1.49%	3.15%	1.48%	3.15%	1.27%	3.22%	1.59%
	t + 9	2.48%	1.49%	3.15%	1.48%	3.15%	1.28%	3.23%	1.58%
	t + 10	2.49%	1.51%	3.14%	1.48%	3.16%	1.27%	3.25%	1.58%
Other Financials									
	t + 1	5.30%	1.49%	3.57%	1.63%	2.14%	1.31%	2.14%	1.31%
	t + 2	3.63%	1.51%	2.87%	1.76%	2.32%	1.36%	2.32%	1.36%
	t + 3	2.99%	1.53%	3.07%	1.69%	2.39%	1.26%	2.39%	1.26%
	t + 4	3.14%	1.53%	3.05%	1.61%	2.49%	1.21%	2.49%	1.21%
	t + 5	3.02%	1.51%	3.16%	1.65%	2.57%	1.34%	2.57%	1.34%
	t + 6	3.00%	1.43%	2.99%	1.53%	2.67%	1.24%	2.67%	1.24%

(*continued on next page*)

Table 7 (*continued*)

Region	Response period	North America		Europe		UK		Asia	
		CDS response to Stocks	Stocks response to CDS	CDS response to Stocks	Stocks response to CDS	CDS response to Stocks	Stocks response to CDS	CDS response to Stocks	Stocks response to CDS
	t + 7	3.18%	1.43%	3.06%	1.52%	2.67%	1.21%	2.67%	1.21%
	t + 8	3.15%	1.43%	3.04%	1.53%	2.67%	1.21%	2.67%	1.21%
	t + 9	3.11%	1.43%	3.03%	1.54%	2.67%	1.23%	2.67%	1.23%
	t + 10	3.13%	1.44%	3.03%	1.54%	2.68%	1.22%	2.68%	1.22%
Services									
	t + 1	2.19%	1.44%	3.66%	1.27%	2.08%	1.18%	5.23%	1.66%
	t + 2	2.13%	1.43%	3.83%	1.38%	2.15%	1.27%	4.60%	1.67%
	t + 3	2.33%	1.39%	3.93%	1.33%	2.11%	1.21%	3.70%	1.63%
	t + 4	2.40%	1.38%	3.98%	1.26%	2.31%	1.12%	2.99%	1.58%
	t + 5	2.59%	1.38%	3.96%	1.30%	2.22%	1.19%	3.29%	1.64%
	t + 6	2.65%	1.31%	3.99%	1.24%	2.21%	1.16%	3.12%	1.58%
	t + 7	2.69%	1.33%	3.95%	1.22%	2.22%	1.14%	3.30%	1.58%
	t + 8	2.71%	1.36%	3.94%	1.21%	2.20%	1.13%	3.36%	1.58%
	t + 9	2.73%	1.36%	3.93%	1.22%	2.19%	1.14%	3.40%	1.59%
	t + 10	2.74%	1.37%	3.93%	1.22%	2.20%	1.14%	3.34%	1.58%
Communications									
	t + 1	2.23%	1.06%	4.60%	1.18%	3.39%	1.51%	4.72%	1.00%
	t + 2	2.20%	1.08%	3.40%	1.18%	2.93%	1.47%	4.56%	1.00%
	t + 3	2.36%	0.98%	2.95%	1.09%	3.06%	1.32%	4.36%	1.02%
	t + 4	2.53%	0.98%	3.41%	1.02%	3.12%	1.23%	4.48%	0.96%
	t + 5	2.52%	1.00%	3.76%	1.05%	3.16%	1.28%	4.60%	0.96%
	t + 6	2.68%	0.96%	3.26%	0.97%	3.20%	1.17%	4.63%	0.90%
	t + 7	2.64%	0.94%	3.34%	0.98%	3.18%	1.18%	4.64%	0.91%
	t + 8	2.66%	0.95%	3.48%	0.99%	3.18%	1.20%	4.63%	0.91%
	t + 9	2.66%	0.96%	3.42%	1.00%	3.18%	1.21%	4.63%	0.91%
	t + 10	2.66%	0.95%	3.35%	0.99%	3.18%	1.20%	4.63%	0.91%
Transportation									
	t + 1	9.17%	1.89%	2.82%	2.38%	*N/A*	*N/A*	3.76%	1.08%
	t + 2	7.02%	1.84%	2.99%	2.41%	*N/A*	*N/A*	3.64%	1.06%
	t + 3	5.97%	1.80%	3.19%	2.45%	*N/A*	*N/A*	3.74%	1.00%
	t + 4	6.01%	1.78%	3.24%	2.40%	*N/A*	*N/A*	4.02%	0.95%
	t + 5	5.95%	1.75%	3.04%	2.45%	*N/A*	*N/A*	4.22%	0.95%
	t + 6	5.61%	1.74%	3.14%	2.39%	*N/A*	*N/A*	4.29%	0.95%
	t + 7	5.81%	1.74%	3.11%	2.38%	*N/A*	*N/A*	4.29%	0.95%
	t + 8	5.86%	1.73%	3.11%	2.37%	*N/A*	*N/A*	4.33%	0.95%
	t + 9	5.82%	1.73%	3.12%	2.37%	*N/A*	*N/A*	4.35%	0.95%
	t + 10	5.83%	1.73%	3.10%	2.37%	*N/A*	*N/A*	4.35%	0.95%

This table shows the impulse response of the CDS sectoral indices, and the underlying stock portfolios returns for the North America, Europe, Asia, and UK regions, to Cholesky one standard deviation shocks to each other and their lagged values. '*N/A*' indicates that data is not available.

In addition, motivated by our empirical results that indicate that the stock market leads the CDS market, we follow Marsh and Wagner (2015) to examine whether it is the positive or negative equity market returns that drive this lead-lag relation. In particular, we run the following regression equation:

$$R_{CDS,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S\_pos,t-i} + \sum_{i=1}^{L}\delta_i R_{S\_neg,t-i} + \varepsilon_t \tag{2}$$

where $R_{CDS,t}$ is the weekly spread of an equally-weighted portfolio of the CDS indices at time t, $R_{S\_pos,t}$ is the weekly positive return of the underlying equally-weighted stock portfolio at time t, $R_{S\_neg,t}$ is the weekly negative return of the underlying equally-weighted stock portfolio at time t, and L (= 3) is the lag length. The α is the intercept term, β_i, γ_i, and δ_i are the coefficients to be estimated, and ε_t is the error term. The results are reported in Table 12. Unsurprisingly, most of the coefficient estimates are negative and statistically significant at various significance levels for both the positive and negative stock lagged returns and for all regions. Further, the coefficient estimates for the positive lagged stock returns tend to be larger in absolute value and statistically more significant. Although the evidence is not clear cut enough, there are indications that the stock market leads the CDS market following negative news and not so following positive news; this is consistent with Marsh and Wagner (2015).

Likely explanations for the stock market lead in the price discovery process might include the high trading cost in the CDS market, the slow diffusion of information across the different economic sectors, the possibility of nonsynchronous trading, and/or a strong nonlinear relation between the CDS and the stock market; see section 2 for a detailed discussion of these possible explanations. Our findings can be compared to the findings of earlier studies. In particular, our results are similar

Table 8
The relation between the weekly spread changes of an equally-weighted portfolio of the CDS indices' and the underlying equally-weighted stock portfolio-underlying stock portfolios' weekly returns: North America.

	Lagged CDS spread changes			Lagged stock returns				
	β_1	β_2	β_3	γ_1	γ_2	γ_3	*N*	Granger
Panel A: Equally-Weighted portfolio							338	
CDS	−0.008 (−0.300)	0.018 (0.711)	0.019 (0.748)	−0.325 (−7.861**)	−0.154 (−3.653**)	−0.099 (−2.375**)		5.308 (0.001)
Stock	0.005 (0.357)	−0.008 (−0.536)	0.042 (2.794**)	−0.038 (−1.489)	−0.021 (−0.816)	0.003 (0.134)		1.805 (0.146)
Panel B: Time periods								
January 2008-March 2011							170	
CDS	0.255 (6.657**)	0.041 (1.039)	0.040 (1.135)	−0.221 (−6.479**)	−0.037 (−1.058)	−0.035 (−1.047)		4.022 (0.009)
Stock	−0.019 (−0.465)	−0.030 (−0.697)	0.115 (2.892**)	−0.044 (−1.167)	−0.072 (−1.827*)	0.045 (1.198)		2.131 (0.098)
April 2011-June 2014							170	
CDS	−0.098 (−2.743**)	−0.031 (−0.876)	−0.013 (−0.366)	−0.393 (−3.565**)	−0.309 (−2.795**)	−0.190 (−1.710*)		3.642 (0.014)
Stock	0.018 (1.009)	−0.001 (−0.147)	0.013 (1.201)	−0.026 (−0.728)	0.113 (3.179**)	−0.116 (−3.229**)		1.256 (0.291)

This table presents the estimates of the following bivariate vector autoregressive model:
$R_{CDS,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S,t-i} + \varepsilon_t$
$R_{S,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S,t-i} + \varepsilon_t$
where $R_{CDS,t}$ is the changes in the weekly spread of an equally-weighted portfolio of the Thompson Reuters CDS indices at time *t*, $R_{S,t}$ is the weekly return of the underlying equally-weighted stock portfolio at time *t*, and *L* (= 3) is the lag length. The α is the intercept term, β_i and γ_i are the coefficients to be estimated respectively, and ε_t is the error term. The *t*-statistics of the coefficient estimates are given in parentheses below the estimates. '*', and '**' denote statistical significance at the 5% and 1% level respectively. The '*N*' is the number of data points, and 'Granger' is the *F*-statistic (*p*-value in parenthesis) of the null hypothesis that all estimated coefficients are statistically equal to zero.

Table 9
The relation between the weekly spread changes of an equally-weighted portfolio of the CDS indices' and the underlying equally-weighted stock portfolio-underlying stock portfolios' weekly returns: Europe.

	Lagged CDS spread changes			Lagged stock returns				
	β_1	β_2	β_3	γ_1	γ_2	γ_3	*N*	Granger
Panel A: Equally-Weighted portfolio							338	
CDS	0.009 (0.331)	0.044 (1.623)	−0.001 (−0.064)	−0.441 (−9.606**)	−0029 (−0.629)	−0.023 (−0.507)		2.896 (0.035)
Stock	−0.000 (−0.046)	−0.039 (−2.431**)	0.030 (1.930*)	0.043 (1.590)	−0.068 (−2.440**)	−0.051 (−1.836*)		1.653 (0.177)
Panel B: Time periods								
January 2008-March 2011							170	
CDS	0.132 (3.379**)	0.035 (0.887)	−0.000 (−0.018)	−0.327 (−5.350**)	0.048 (0.777)	−0.048 (−0.776)		11.022 (0.000)
Stock	−0.024 (−0.990)	−0.025 (−0.991)	0.033 (1.368)	0.016 (0.411)	−0.093 (−2.329**)	−0.017 (−0.438)		0.886 (0.450)
April 2011-June 2014							170	
CDS	−0152 (−3.957**)	0.016 (0.434)	−0.008 (−0.220)	−0.613 (−8.703**)	−0.188 (−2.559**)	0.001 (0.014)		8.522 (0.000)
Stock	0.026 (1.295)	−0.051 (−2.456**)	0.021 (1.112)	0.087 (2.305**)	−0.017 (−0.445)	−0.114 (−2.881**)		1.321 (0.269)

This table presents the estimates of the following bivariate vector autoregressive model:
$R_{CDS,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S,t-i} + \varepsilon_t$
$R_{S,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S,t-i} + \varepsilon_t$
where $R_{CDS,t}$ is the changes in the weekly spread of an equally-weighted portfolio of the Thompson Reuters CDS indices at time *t*, $R_{S,t}$ is the weekly return of the underlying equally-weighted stock portfolio at time *t*, and *L* (= 3) is the lag length. The α is the intercept term, β_i and γ_i are the coefficients to be estimated respectively, and ε_t is the error term. The *t*-statistics of the coefficient estimates are given in parentheses below the estimates. '*', and '**' denote statistical significance at the 5% and 1% level respectively. The '*N*' is the number of data points, and 'Granger' is the *F*-statistic (*p*-value in parenthesis) of the null hypothesis that all estimated coefficients are statistically equal to zero.

Table 10
The relation between the weekly spread changes of an equally-weighted portfolio of the CDS indices' and the underlying equally-weighted stock portfolio-underlying stock portfolios' weekly returns: UK.

	Lagged CDS spread changes			Lagged stock returns				
	β_1	β_2	β_3	γ_1	γ_2	γ_3	N	Granger
Panel A: Equally-Weighted portfolio							338	
CDS	0.010 (0.391)	0.044 (1.626)	0.016 (0.611)	−0.379 (−9.093**)	0.001 (0.044)	−0.046 (−1.087)		13.653 (0.000)
Stock	0.004 (0.233)	−0.005 (−0.292)	0.036 (2.072*)	0.028 (1.033)	−0.076 (−2.707**)	−0.029 (−1.054)		1.800 (0.147)
Panel B: Time periods								
January 2008-March 2011							170	
CDS	0.068 (1.775*)	0.029 (0.767)	0.029 (0.793)	−0.352 (−6.196**)	0.036 (0.631)	−0.056 (−0.981)		7.866 (0.000)
Stock	−0.003 (−0.138)	−0.007 (−0.304)	0.044 (1.770)	0.014 (0.362)	−0.093 (−2.360**)	−0.023 (−0.594)		1.539 (0.204)
April 2011-June 2014							170	
CDS	−0.141 (−3.525**)	0.040 (1.012)	−0.012 (−0.318)	−0.472 (−7.194**)	−0.122 (−1.818*)	−0.037 (−0.555)		5.886 (0.001)
Stock	0.029 (1.207)	0.005 (0.208)	0.011 (0.495)	0.077 (1.938*)	−0.020 (−0.485)	−0.053 (−1.288)		2.001 (0.114)

This table presents the estimates of the following bivariate vector autoregressive model:

$R_{CDS,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S,t-i} + \varepsilon_t$

$R_{S,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S,t-i} + \varepsilon_t$

where $R_{CDS,t}$ is the changes in the weekly spread of an equally-weighted portfolio of the Thompson Reuters CDS indices at time t, $R_{S,t}$ is the weekly return of the underlying equally-weighted stock portfolio at time t, and L (= 3) is the lag length. The α is the intercept term, β_i and γ_i are the coefficients to be estimated respectively, and ε_t is the error term. The t-statistics of the coefficient estimates are given in parentheses below the estimates. '*', and '**' denote statistical significance at the 5% and 1% level respectively. The 'N' is the number of data points, and 'Granger' is the F-statistic (p-value in parenthesis) of the null hypothesis that all estimated coefficients are statistically equal to zero.

Table 11
The relation between the weekly spread changes of an equally-weighted portfolio of the CDS indices' and the underlying equally-weighted stock portfolio-underlying stock portfolios' weekly returns: Asia.

	Lagged CDS spread changes			Lagged stock returns				
	β_1	β_2	β_3	γ_1	γ_2	γ_3	N	Granger
Panel A: Equally-Weighted portfolio							338	
CDS	0.062 (2.228*)	0.137 (4.939**)	0.029 (1.067)	−0.271 (−4.697**)	0.142 (2.450**)	−0.040 (−0.687)		3.485 (0.016)
Stock	−0.041 (−3.121**)	−0.044 (−3.337**)	0.007 (0.577)	−0.012 (−0.433)	−0.063 (−2.274*)	−0.052 (−1.881*)		0.996 (0.395)
Panel B: Time periods								
January 2008-March 2011							170	
CDS	0.135 (3.216**)	0.193 (4.621**)	0.042 (1.022)	−0.256 (−2.906**)	0.301 (3.385**)	−0.004 (−0.045)		6.338 (0.000)
Stock	−0.059 (−2.980**)	−0.058 (−2.929**)	0.009 (0.497)	−0.048 (−1.155)	−0.131 (−3.118**)	−0.066 (−1.558)		0.855 (0.466)
April 2011-June 2014							170	
CDS	−0.144 (−4.029**)	−0.012 (−0.350)	−0.050 (−1.407)	−0.194 (−2.756**)	−0.090 (−1.283)	−0.104 (−1.485)		4.966 (0.003)
Stock	−0.019 (−1.047)	−0.035 (−1.923*)	0.004 (0.236)	0.024 (0.676)	0.045 (1.267)	−0.035 (−0.996)		1.508 (0.214)

This table presents the estimates of the following bivariate vector autoregressive model:

$R_{CDS,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S,t-i} + \varepsilon_t$

$R_{S,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S,t-i} + \varepsilon_t$

where $R_{CDS,t}$ is the changes in the weekly spread of an equally-weighted portfolio of the Thompson Reuters CDS indices at time t, $R_{S,t}$ is the weekly return of the underlying equally-weighted stock portfolio at time t, and L (= 3) is the lag length. The α is the intercept term, β_i and γ_i are the coefficients to be estimated respectively, and ε_t is the error term. The t-statistics of the coefficient estimates are given in parentheses below the estimates. '*', and '**' denote statistical significance at the 5% and 1% level respectively. The 'N' is the number of data points, and 'Granger' is the F-statistic (p-value in parenthesis) of the null hypothesis that all estimated coefficients are statistically equal to zero.

Table 12
Asymmetric CDS spread changes response to positive and negative stock market returns.

	Lagged positive stock returns			Lagged negative stock returns				
	γ_1	γ_2	γ_3	δ_1	δ_2	δ_3	N	Adjusted R^2
Panel A: North America								
CDS spread changes	−0.018 (−1.810*)	−0.101 (−2.111*)	0.029 (1.608)	−0.245 (−3.231**)	−0.104 (−1.683)	−0.059 (−1.975*)	338	0.198
Panel B: Europe								
CDS spread changes	−0.108 (−1.820*)	−0.088 (−1.711*)	−0.009 (0.728)	−0.325 (−5.151**)	−0.166(−3.003**)	−0.059 (−1.375)	338	0.301
Panel C: UK								
CDS spread changes	−0.108 (−2.210**)	0.008 (0.851)	−0.018 (−0.598)	−0.215 (−4.098**)	−0.094 (−2.353**)	−0.050 (−1.878*)	338	0.105
Panel D: Asia								
CDS spread changes	−0.198 (−2.551**)	0.097 (1.759*)	−0.019 (−0.708)	−0.225 (−5.161**)	−0.189 (−2.835**)	−0.059 (−1.975*)	338	0.465

This table presents the estimates of the following regression model:
$R_{CDS,t} = a + \sum_{i=1}^{L}\beta_i R_{CDS,t-i} + \sum_{i=1}^{L}\gamma_i R_{S\_pos,t-i} + +\sum_{i=1}^{L}\delta_i R_{S\_neg,t-i} + \varepsilon_t$
where $R_{CDS,t}$ is the weekly spread of an equally-weighted portfolio of the CDS indices at time t, $R_{S\_pos,t}$ is the weekly positive return of the underlying equally-weighted stock portfolio at time t, $R_{S\_neg,t}$ is the weekly negative return of the underlying equally-weighted stock portfolio at time t, and L (= 3) is the lag length. The α is the intercept term, β_i, γ_i, and δ_i are the coefficients to be estimated, and ε_t is the error term. The t-statistics of the coefficient estimates are given in parentheses. '*', and '**' denote statistical significance at the 5% and 1% level respectively. The 'N' is the number of data points used in the estimation of the coefficients.

to Byström (2008) who examines the relation between seven European sectoral iTraxx CDS indices (i.e., Autos, Industrials, Energy, Consumers, Technology-Media-Telecommunications, Senior Financial, and Sub-ordinated Financials) and the underlying stock portfolios, and also reports that the stock market incorporates firm-specific information faster than the CDS market. Norden and Weber (2004), find that stock returns lead CDS spreads for the case of 58 firms from Europe, US and Asia. Further, our results compliment those of Norden and Weber (2009) and Forte and Peña (2009) who also find that the stock market clearly leads the CDS market. However, our results partially collaborate the results by Longstaff et al., (2003) who find a rather unclear relation between the stocks and CDS in the US market. For example, we also fail to find evidence that stock returns lead CDS spreads in the Electric Power sector, while we also present some evidence that CDS spreads affect the stock returns in the Banks, Energy, Services, and Communications sectors; similar findings are reported by Flannery et al. (2010). It should also be noted that our findings strongly support Hilscher et al. (2015) who find that the stock returns lead the credit protection returns. They also argue that this is consistent with standard theories on market selection (e.g., Easley et al., 1998). Specifically, our results support the argument that there is a separating equilibrium in which informed traders prefer to trade default risk mostly or only in the stock market, and uninformed traders trade mostly in the CDS market. Thus, if the informed traders prefer to trade in the stock market, then this market reflects the most recent information related to the changing default risk, and a lead-lag relation is observed between the stock and the CDS markets. Thus our results might be interpreted as an indication of the presence of informed traders in the stock market and the general absence of informed traders in the CDS market.[25,26] Overall, our results strongly indicate that the stock market leads the price discovery process in all of the different regions and their economic sectors. On the other hand, there is considerably less evidence of a feedback effect that stems from the CDS market to the stock market. Thus, the stock market is more efficient in processing information relative to the CDS market. This finding implies that the stock market prices faster than the CDS market the sectoral default risk.

5. Conclusion

We examine whether default risk is priced equally fast by the CDS and the stock markets. We use a comprehensive data set of CDS indices obtained from Thomson Reuters and the manually constructed underlying stock portfolios. This data set covers nine main economic sectors in North America, Europe, the UK, and Asia over the time period from January 1, 2008, to June 30, 2014.

Our results strongly indicate that in all of the geographical regions and across the different economic sectors the stock market leads the CDS market in the price discovery process; and therefore the stock market is relatively more efficient than the CDS market. This finding implies that the stock market prices the changing default risk faster than the CDS market at economic sector level. We also detect no significant feedback effect from the CDS market to the stock market. This finding

[25] In general, informed traders prefer to trade in the market in which, (i) the security they want to trade has high sensitivity to the release of the information they hold, (ii) transaction costs are low, and (iii) there is a high proportion of uninformed traders.

[26] Our results are also relevant to the literature that is related to the association between stocks and bonds. Hong et al. (2012), Gebhardt et al. (2005), Downing et al. (2009), and Kwan (1996) find that the stock market is relatively more efficient than the bond market. Further, Blanco et al. (2005), Norden and Weber (2009), Forte and Peña (2009), and Zhu (2006) find that the price discovery in the bond market lags the price discovery in the associated CDS and stock markets. Thus, it seems that the CDS spreads lead the bond discovery process (also argued by Hilscher et al. (2015)).

is consistent with the market selection theories according to which there is a separating equilibrium in which informed traders prefer to trade default risk mostly or only in the stock market, and uninformed traders trade mostly in the CDS market. As a result the stock market reflects the most recent information that is related to the changing default risk. Our results are important to both practitioners and policy-makers. In particular, a significant lead-lag relation between the two markets implies informational inefficiencies and signals profitable opportunities from trades in the two markets. Further, insights into the relative efficiency of the CDS and stock markets might be used for better monitoring of the default-risk risk transference and to promote policies that might enhance informational efficiency. Possible reasons for the stock market lead in the price discovery process might include the high trading cost in the CDS market, the slow diffusion of information across the different economic sectors, the possibility of nonsynchronous trading, and/or a strongly nonlinear relation between the CDS and the stock market. Although beyond the scope of this paper, an examination of the role of these factors in the lead-lag relation between the CDS and the stock market is an interesting venue for future research.

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